MEDICAL IMAGE INDEXING AND COMPRESSION BASED ON VECTOR QUANTIZATION: IMAGE RETRIEVAL EFFICIENCY EVALUATION

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***Abstract* – This paper addresses the problem of efficient image retrieval from a compressed image database, using information derived from the compression process. Images in the database are compressed applying two approaches: Vector Quantization (VQ) and Quadtree image decomposition. Both are based on Konohen's Self-Organizing Feature Maps (SOFM) for creating vector quantization codebooks. However, while VQ uses one codebook of one resolution to compress the images, Quadtree decomposition uses simultaneously 4 codebooks of four different resolutions. Image indexing is implemented by generating a Feature Vector (FV) for each compressed image. Accordingly, images are retrieved by means of FVs similary evaluation between the query image and the images in the database, depending on a distance measure. Three distance measures have been analyzed to assess FV index similarity: Euclidean, Intersection and Correlation distances. Distance measures efficiency retrieval is evaluated for different VQ resolutions and different Quadtree image descriptors. Experimental results using real data, esophageal ultrasound and eye angiography images, are presented.**
***Keywords* - Image Indexing, Content-Based Image Retrieval, Vector Quantization, Quadtree.**

I. INTRODUCTION

Medical image analysis and exploitation are fundamental for diagnostic and therapy purposes. Nowadays, besides medical images on film, digitized images are becoming more frequently used. This leads in growing requirements for storage and/or transmission time, because of the increasing number of images to be stored/transmitted, as well as the need to avoid information lost. As a consequence, compression and indexing of medical images are crucial questions, particularly when they are related to image retrieval from multimedia databases. Several image-indexing techniques have been proposed in the literature [1]-[3]. Two approaches are commonly used: (i) content indexing, on which the index terms serve to encode image content, and (ii) content structuring, on which images are represented as a hierarchy of regions, objects, and portions of objects. The content indexing approach is based on image features such as color, texture, shape and sketch that are used as indexes. On the other hand, the content structuring approach is based on spatial relationships between objects or regions in a scene.

Our objective is to achieve medical image retrieval from compressed databases, using one compressed image as reference to perform the query, evaluating the results quality through the application of an efficiency measurement. Content indexing has been retained to carry out image indexing and retrieval, because it allows to create image descriptors when images are compressed, avoiding thus, image decompression during the searching process.

In content indexing approaches a feature is selected according to the following criteria: i) its capacity to distinguish different images, ii) the maximum number of images a query could possibly retrieve, and iii) the amount of computation required to calculate (or the amount of space required to store them) and compare features. Generally, a multidimensional Feature Vector (FV) is obtained for each image, and indexing is calculated depending on FVs similarities. Given the various features interpretation and quantification fuzziness, emphasis is therefore made on similarity rather than exactness of the obtained FVs.

A vector Quantization (VQ) scheme has been chosen to create image descriptors. It has the particular characteristic of exploiting images *a priori* knowledge. Namely, a codebook obtained from a training set, i.e. several images that are representative of the image database, has to be generated before compression. Moreover, appropriate codebooks can be produced, leading to use VQ in an efficient manner [4], [5].

This work analyzes the application of VQ and multi-resolution VQ Quadtree compression schemes, associated to FVs indexation. Furthermore, retrieval efficiency is evaluated through three distance measures: Euclidean, Intersection and Correlation distances. The rest of the paper is organized as follows. Section II remembers the compression methodology based on standard VQ and Quadtree algorithms. Section III presents the general indexation and retrieval scheme. Image retrieval efficiency evaluation is described in section IV. Results are reported in Section V. Finally, our approach is discussed along with concluding remarks on section VI.

II. COMPRESSION METHODOLOGY

A. Vector Quantization

VQ is an efficient technique for low bit rate image and video compression. In the VQ algorithm (Fig. 1), the image to be compressed is partitioned into small non-overlapping

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blocks or vectors. A VQ encoder maps each input vector onto one finite set of codewords (codebook) using a nearest neighbor rule [6]. Codeword labels are then used to represent the input image. A VQ decoder reconstructs the input image using a look-up table. Given its decoder simplicity, VQ is attractive for applications where images are compressed once and potentially decompressed multiple times at different sites.

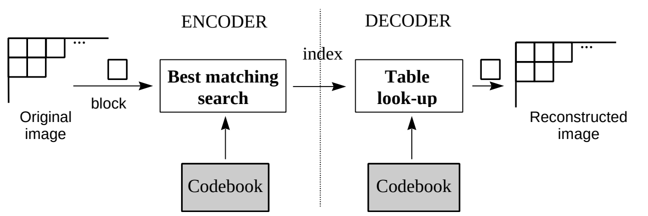

Fig. 1. VQ encoder and decoder.

We use the Kohonen's Self Organizing Feature Map (SOFM) to generate adapted codebooks [7]. Some of the SOFM interesting properties are: i) Self-organizing algorithm, which does not need to classify the training image blocks (unsupervised learning). ii) Ability to form ordered topological feature maps: neighbor neurons in the map have neighbor weight vectors in the gray-level pixel space, given that they are visually similar. Therefore, it is possible to perform a classification of pixels in the image, by directly segmenting the Kohonen's maps. iii) Preservation of image blocks visual aspect, which is very important for strong textured images.

B. Quadtree

Quadtree image decomposition is often used to analyze and segment images according to chosen features, like for example homogeneity or texture parameters. In the proposed scheme, matching of different size codewords is tested with blocks of the image to encode. We have used 4 codebooks with codewords (pixel blocks) of size 16x16, 8x8, 4x4 and 2x2. These codebooks are independently generated using the SOFM algorithm, by means of 16x16 neurons neural maps. Each one of the four codebooks contains 256 codewords. Hence, one byte labels design each codeword. Wherever it is possible, large codewords are used to obtain high compression rates. Smaller blocks are used elsewhere, depending on the Quadtree decomposition.

After dividing the image into 16x16 pixel blocks, the codeword of size 16x16, which is the closest to the studied block, in the sense of the Euclidean distance, is searched. If the distance between the studied block and the codeword is less than a predefined threshold, the studied block is coded by this codeword. If not, the 16x16 studied block is divided into four blocks of 8x8 pixels. The process is iterated, until the whole block is encoded, using 2x2 codewords if justified (Fig. 2). Clearly, the thresholds are very important parameters, since they determine the tradeoff between compression rate and reconstruction quality. Low thresholds lead to low compression rates and good image quality, while higher thresholds result in higher compression rates and lower image quality. This algorithm is referred to as VQQT (Vector Quantization with a Quadtree scheme) and leads to a variable rate coding procedure, which includes complementary information describing the Quadtree decomposition of the image [6].

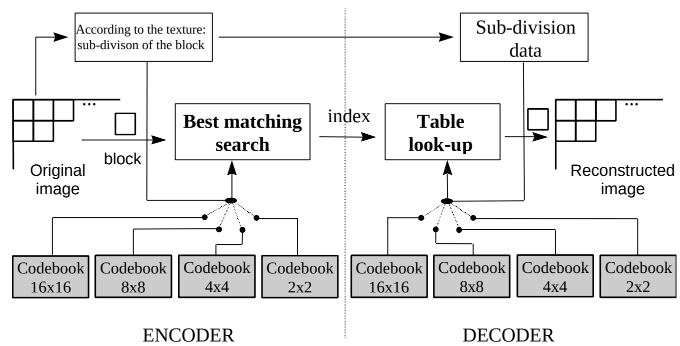

Fig. 2. Quadtree encoder and decoder.

III. INDEXATION AND RETRIEVAL

A matrix $[m_{ij}]$ with the same topology of the SOFM codebook is used as image descriptor or FV. Each m_{ij} value is the number of occurrences in the compressed image, of the codevector at positions (i,j) in the SOFM, i.e. the FV is a 2D histogram of the codevectors' occurrence. Images are subsequently indexed using the FV. Since image retrieval is based on FV index similarity, a distance measure has to be defined. Three distance measures have been analyzed to evaluate FV index similarity: Euclidean (1), Intersection (2) and Correlation distances (3):

$$d_{euclid}(P,Q) = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(p_{ij} - q_{ij}\right)^2} \quad (1)$$

$$d_{inter}(P,Q) = \sum_{i=1}^{n}\sum_{j=1}^{n} min\left(p_{ij}, q_{ij}\right) \quad (2)$$

$$d_{corr}(P,Q) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(p_{ij} - \tilde{p}\right)\left(q_{ij} - \tilde{q}\right)}{\left[\sum_{i=1}^{n}\sum_{j=1}^{n}\left(p_{ij} - \tilde{p}\right)^2 \sum_{i=1}^{n}\sum_{j=1}^{n}\left(q_{ij} - \tilde{q}\right)^2\right]^{1/2}} \quad (3)$$

Where P and Q represent the matrix $[m_{ij}]$, for the query image and the database image respectively; $\tilde{p}$ and $\tilde{q}$ are the mean value of each matrix. Thus, the image retrieval is made by calculating the "distance" between the query FV and that of each image in the database.

Our VQ based indexing technique, only uses one FV per image in the comparison process. As a consequence, retrieval performance is tested for separated codewords resolutions and for different similitude metrics. In the Quadtree based scheme we employ four FVs, one for each resolution, 16x16, 8x8, 4x4, 2x2. Indexing is based on a normalized average of the four resolution distances, which is used to make a selection based on the minimal distance. Additionally, in this approach we investigate the utilization of the *decomposition image*. It is formed from Quadtree information in the following way: for each 2x2 block one pixel is coded. This pixel score is 0 if the block that it represents has been coded using one codeword of size 16x16; 1 if a 8x8 codeword was used, 2 if a 4x4 codeword was used, or 3 if a 2x2 codeword was used. Afterwards, the comparison between the query decomposition image and the decomposition images in the databases is made using an Euclidean distance.

IV. Retrieval Efficiency Evaluation

Retrieval efficiency h_r is applied as a retrieval performance criterion [8]. In our particular case it takes into account the following elements. For each image *i*, in a database of size *K*, similar images contained in the database are initially identified, being N_i, $1 \le i \le K$, the number of such images. We then apply an indexing technique for a query image-*q*, and retrieve the first $(N_q + t)$ images, where *t* is a positive integer, understood as the retrieval tolerance. If n_q is the number of successfully retrieved images, the retrieval efficiency can then be defined as:

$$h_r = \frac{\sum_{q=1}^{K} n_q}{\sum_{q=1}^{K} N_q} \quad (4)$$

Equation (4) gives the average of retrieval efficiency of the whole database, i.e., the percentage of obtained good reponses with regard to N_i.

V. Results

The proposed compression, indexation and retrieval schemes have been tested on 2 different medical image databases: i) ultrasonic images of the esophagus and ii) angiographic images of the retina. The echo-endoscopic database is a spatial sequence of 88 images acquired from one esophagus. Given a characteristic pathology like a tumor, our goal is to retrieve the closest image to the query image along with its related predecessors and successors. The angiographic database is composed of 40 injected retina images, classified in 8 classes representing specific pathologies. All images are 256 gray level and a tolerance *t* of 5 has been used to compute the retrieval efficiency (4), for both databases. Thresholds have been fixed to give compression rates on the average of 16 and PSNR ≥ 30 dB, i.e., a good quality compressed image.

Fig. 3 shows the retrieval efficiency for the echo-endoscopic database using separated FVs obtained from VQ compression scheme. Results are shown as a function of the resolution (codeword size) and the similitude metric. The same applies to Fig. 4, where the retrieval efficiency for the database of angiographies is depicted.

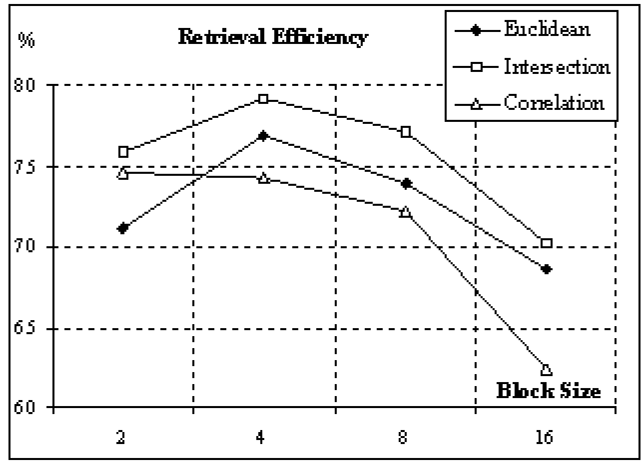

Fig. 3. Retrieval efficiency vs. size of codeword for the echo-endoscopic database using VQ indexing scheme.

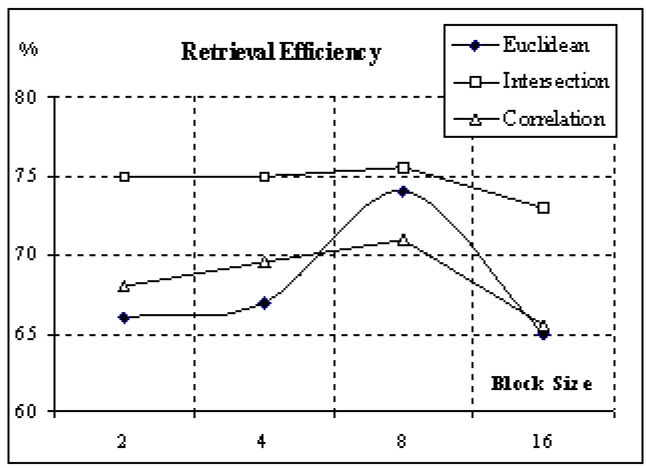

Fig. 4. Retrieval efficiency vs. size of codeword for the angiographies' database using VQ indexing scheme.

TABLE I
% of Retrieval efficiency - Quadtree algorithm

	Endoscopies	Angiographies
Euclidean	62.90	77.00
Intersection	61.80	66.00
Correlation	46.14	80.50
Decomposition	84.77	68.00

Table I presents the percentage of retrieval efficiency obtained for the Quadtree compression-indexing scheme. The three first three rows correspond to efficiency results comparing the similarity of normalized FVs with the indicated similitude metric. The last row presents the retrieval efficiency of the decomposition image used as image descriptor, evaluated with the Euclidean distance.

On Fig. 5 and 6, the quadtree decomposition images, the four FVs, and the retrieval results for a specific query of the echo-endoscopic esophagus and angiography images are shown. FV bright blocks illustrate high codeword occurrences, while dark blocks correspond to low occurrences.

VI. Discussion and Conclusion

The proposed methods allow to quickly (≈ 2 sec.) retrieve answers to the query image in the compressed image database, with reasonable accuracy. For echo-endoscopic images, the algorithms finds images, which are spatially close to the query image. In addition, for the angiographic database it is possible to identify similar images in the same pathology class, to which the query image belongs to. These results show that the FVs are characteristic of the compressed image, because they are dissimilar for any pair of different images. Therefore, they can be used as image descriptors for image indexing retrieval by content. In the particular case of VQ compressed-indexed images, the intersection measure appears to be the best FVs similitude metric.

The utilization of spatial information obtained from multi-resolution Quadtree scheme gives somewhat paradoxical results, considering that the best and the worst retrieval efficiencies (Table I) are obtained when the scheme is applied. This means that the algorithms are more sensible to both, image characteristics and the used metric. Moreover, once the right parameters (FV or decomposition image and metric) have been chosen, it overcomes the results obtained with VQ. When images are very similar, like in the echo-endosocpic sequence, the decomposition image provides the required details to differentiate them. Nevertheless, when images are not similar, like in the case of eye angiographies, on which rotations, small translations and illumination variations define the differences, use of FVs is more efficient because of their best invariance to these factors.

Further application of indexing-retrieval schemes concern color video-endoscopic images, wavelet oriented feature extraction according to the new JPEG-2000 standard, as well as processing of MPEG-7 descriptors, combined with knowledge-based approaches.

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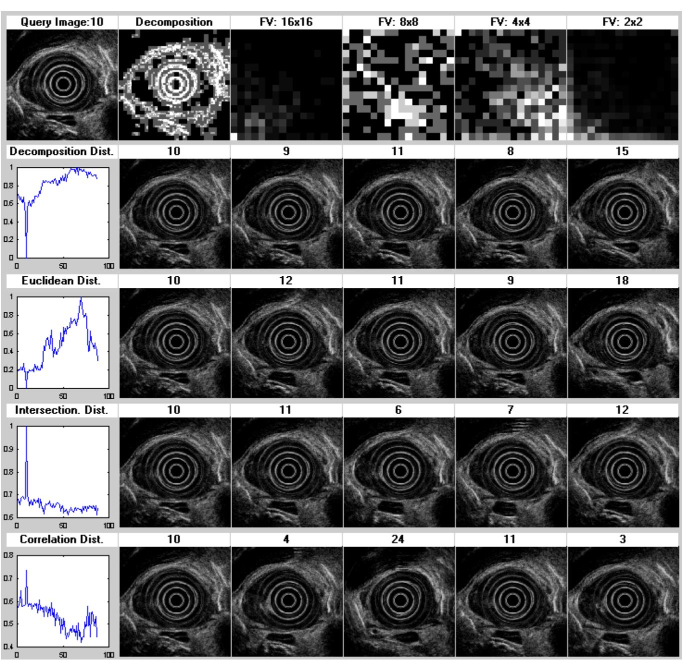

Fig. 5. Retrieval results of indexing algoritms in echo-endoscopic database using Quadtree compression information.

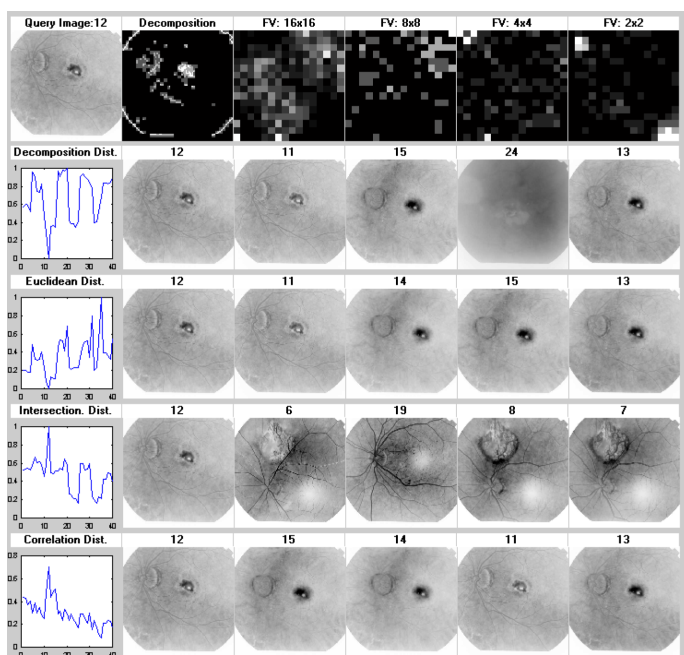

Fig. 6. Retrieval results of indexing algoritms in angiographies’ database using Quadtree compression information.